

Techniques for Judging Intent Behind Network Based Cyber Attacks

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LDRDFinalReport

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Purpose

Thisprojectdevelopedaprototypesystemthatcanrapidlydifferentiatebetweenun - directedcyberattacks, and those that have a more specificand concerning intent behind them. The system responds to important cyberattacks in a tactically significant way as the attack is proceeding. It is also creates a prioritized list for the human analysts allowing them to focus on the threats mostly likely to be of interest. In the recent years the volume of attacks over the internet has increased exponentially, as they have become more and more automated. The result of this is that real threats are harder and harder to

distinguishfromthegeneralth reat. It is possible with our current systems to identify network packets that originated from thousands of IP addresses as probing a sitelike LLNL in a single day. Human analysis of the seth reats does not result in information that can be used for tactic alresponse because most of the attacks are short and over before the human starts the analysis. Only avery small percentage of attacks can even be evaluated manually due to the volume. This project developed methods, and prototy ped tools, that can identify attacks, slow the attack down and aid in the process of prioritizing detections. The project demonstrated that such methods exist, and that practical implementations exist for modern computers and networks. We call the tools created D.I.A.G. or Determining Internet Attackers Goals.

Approach

Theapproachwetookwastocreateasystemtosimulateallormostofthehostsofa protected site and wait for an attack. The system engages the probing hosts by responding totheirprobes, and does so in a way t hattheattackerdoesnotanticipate. The purpose of respondinginanun -anticipatedfashion,istoinducetheattackerintobetrayingadditional informationaboutthemselves and their intentions. We use this additional information to slowdowntheattack alreadyinprogress, as well as to help usclassify the intentof the attacker. The goalisan automatics ystem to recognize skilled attackers and to tell the differencebetweenthoseattackersandthehighlevelofattacknoisefromwormsand scriptsnot directedspecificallyattheprotectedsite. One of the keyideas, is utilize our abilitytogeneratepatternsinthebogusdatathatwerespondwiththatwillbequestioned byaskilledattacker,andignoredasspuriousbyawormorun -attendedscript.On eset carefullyconstructedresultsthatweprovidearecraftedtoappearasiftheremayhave beentheresultofamalfunction. Transient malfunctions are not uncommon crossing the internet. The standard method of resolving such is suesistore peat the pr obeandcompare results. Undirected attacks willignore such spurious data and simply move on, aluxury not afforded to the attacker targeting a site that needs to understand every result. Inessence, wearelooking for indications that the attacker is imp lementingscientific principles of repeatability, to deduce the intent behind the attack. When we can detect these attempts to repeat the probe, we can identify those attacks with this level of analysis behindthem. The time between the initial probe, and theattemptsatestablishing repeatabilitywillalsotellusesomethingabouthowcloselytheprobesarebeing monitored. Tobe practical tode ployatmany sites a scaled upsystem would need to cost lessthan\$100,000percopysowelimitedourselvestod esigningaround, and optimizing for an almost standard highend PChardware. The system used costless than \$15,000 and supported targeted the prototype at a 1:4 scale. At this scale it was able to simulate 65535IPaddressessimultaneouslywithamixofs ervicesonthosehoststhatis statisticallyindistinguishablefromtherealhostsattheprotectedsite.

Accomplishments

1. Weprofiledseveralmonthsofinternetattackactivity, obtaining network packet information from LLNL existing intrusion detection system. We extracted common patterns that we reconsistent over the dataset and used

themtotailorthedatabaseforaveryhighlevelofcompression.Inmanycases thiscompressionyields100:1orgreatercompressionratiosoverthetime horizonofsevera lmonthsofdata.Thiscompressionisimportanttocreatinga systemthatcansimultaneouslysupportfastaccess,maintainstatefor thousandsofsimulatedhosts,andrunonasystemthatispracticaltodeploy. Thishighlevelofcompressionallowedusto storemuchofthedataonthe prototypedirectlyinmemorywhereitcouldbeaccessedquicklyenoughto respondquicklyenoughtosimulatehowarealhostwouldrespond.

- 2. FastinsertionsintotheDBarealsoanecessaryfeatureofkeepingstatefora largenumberofIPaddresses.Forpurposesoftheprototypewewantedto scaletoaclassBnetwork,whichcanaccommodate65,535uniqueIP addressesandincludehistoryforalargenumberofattackers.Wesustained over10,000DBinsertionspersecond,into ourcustomdatabaseonan \$11,000computerthatwasusedfortheprototype.Thiswasaccomplishedby configuringthedatabasetofitastatisticalmodeloftheaverageexpecteddata patterns.Thissignificantlyexceededthescalabilitygoalsforthisaspe ctof theprototypeandshowedthatapracticalsystem,thatwouldprotectalarge sitelikeLLNLispossibleutilizingofftheshelfcomputinghardware.
- 3. WecreatedasimulationoftheLLNLyellownetwork. Wewrotetoolstotake datacollectedatLLNLdu ringsystemvulnerabilityscans, and we used that dataasastatisticalbasistocreatethis prototype deception in such away that in aggregate is blends with the real network because the instance of each host or application type in the deception is ident ical to their instances in the real network. This was also done to be sure that other un -anticipated scaling effects didn't exist in the database. It was successful, and as can of the prototype simulation was statistically consistent with scans of the actual systems.
- 4. WroteatooltomeasuretheOS/applicationtimeoutsinTCPconnections.We accomplishedthisbysimulatingtheactionsoftheoperatingsystem's network stackinourowncode.Wesentrepliesnecessarytokeepeachconnection openatthetrans portlayerwhilesendingnothingattheapplicationlayer.We measuredthetimebetweentheinitialconnectionandthelastcontactfrom the remotehost.Usingthismethodwewereabletoidentifyanumberofdifferent networkscanningtoolsbaseduponthe irbehavior.
- 5. Welaunchedattacksagainsttheprototypesystem. Wecompared the resulting output of the attack tool stothat that we expected them to receive. In these laboratory conditions we were able to sustain network traffic volume equal to that of a large Internet sitelike LLNL, assuming that 80% of the traffic was attack traffic which is well above expected limits as this system is not designed to deal with denial of service attacks. A collection of common hacker tools all returned our crafted results in the expected fashion. We

- compared the scanresults against the deceptions, with the scanresults of actual systems.
- 6. WeputtheprototypeoutontheInternettoseewhathappensagainstreal worldconditions. The prototype was given a couple of IP addresses, and the mostbasicofourdeceptions. The system was allowed to run for 20 days. Duringthattime,11745uniqueSRCIP'ssentsomesortofun -solicited network probest o 1 or more of the IP addresses used by the prototype system.Ofthosedetec ts,9turnedouttobeauthorizedsystems,thatwereexpectedto probeallIP'sattheprotectedsite,leaving11736probesforwhichwedidnot knowtheintent. One of the hypothesis of the project is that Internet worms legalresponsestotheirprobes, butthatan wouldjustignoreourstrangebut intelligentattackerwouldretrytheprobe, and betraytheir existence at the otherend.inanattempttounderstandtheconfusingoutput.Wesortedthe d.The5 th IPonthe 11736detectsbythequantityoftrafficthattheyinvolve list, was a clear success. Human analysis of this detect by both there search team, as well as other intrusion analysts to which the detect was passed reachedtheunanimousconclusionthatitwasclearlyaskilled,knowledgeable attacker, that was monitoring the results of their attack in real time, and applyingscientificprinciplesofrepeatabilitytoattempttodetermineifthe validityoftheresponsestheygotfromtheprototypesystem. The same attackingsystemthatinteractedwit htheprototypesystem, also interacted withanumberofrealsystems, which were used as the control group in this phase of this experiment. When it interacted with one of the control hosts, the probesappearedtobejustastandardwormtypeofscan.It wouldhit1system every60 -120minutes, make a single connection, and a single probe in side that connection. It appears to pick IP addresses a trandom. Traditional signaturebasedIDSsystemsdidnotalertonanyofthecontentsofthepackets tothecont rolhosts. Ahoneypotsystem, would have registered the scan, but beenunabletodifferentiatethisscanfromaworm.ProtocolanalysisIDS systems would not have triggered on the activity to the control host either, as theprobewasalegitfromthatper spectiveaswell.

AComparisonoftheskilledattackerbetweenaregularcontrolhostandthe LDRDprototypewiththemostbasicofit's deceptions.

Attackonarealhost

Connectionsequencedoneonce

Onesourceportused

8packetssentovertwoseco nds

Noknownsignaturebasedalertstriggered

LooksexactlylikeanInternetwormtobothautomatedandhumananalyst.

AttackagainstprototypeprotectedIP Connectionrepeated4times 8differentsourceportsused 37packetssentover33minutesand 52seconds 1Signaturebasedalerttriggered4times

Clearlyanattackbyaskilledattackerwhoislookingattheresultsgenerated, and whoreactsinaknowledgeableandlogicalfashionincludingusingscientificprinciplesto interprettheresponses weprovided to their probes.

Conclusion

TheLDRD'sopeningpremise, is valid. It is possible to supply both the worms of the internet, and the human hackers un -expected, but completely legit responses to their probes, and then tell the difference betwee nthe two by the way they react or don't react to that specially crafted data. The second premise, that we could develop something that would also slow an attacker down enough to constitute at actical defense is also valid. Not only did it work in controlled ed conditions, in the test on the live internetit took an attack that would have lasted only 2 seconds and stretched it out to in excess of 33 minutes. The final premise, that this might even be practical to implemental so turned out to be correct. On ab or rowed \$11,000 computer we were able to simulate an etwork 1/4 the size of LLNL's network with a basic deception which is well under what sites like LLNL pay for other types of intrusion detection devices.